ORIGINAL ARTICLE

Transforming physical healthcare training through integration of machine learning and advanced artificial intelligent methods

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ABSTRACT

Mental healthcare and heart disease continues to be a major cause of death worldwide, making it essential to find effective ways to prevent it. Physical activity has long been known to be important for preventing and treating mental healthcare disease, but it is not always clear how much and what type of activity an individual should do. Artificial intelligence (AI) models that can predict a person's risk of mental healthcare disease based on their individual characteristics have become increasingly popular in recent years. In this study, we used AI models to explore the relationship between physical activity and mental healthcare using data from 100 participants that included information about their demographics, medical history, lifestyle, and environment. Our dataset encompasses crucial variables like age, gender, ethnicity, medical history (including heart disease and high blood pressure), socioeconomic status, physical activity (including type, duration, intensity, and frequency), and environmental factors. In this study we predict the mental healthcare and physical activities effect using machine learning (LR, DT, RF, SVM and KNN) and deep learning (CNN, RNN, TabNet, GAN and DQN) models. We leverage cutting-edge analytics, such as machine learning and deep learning, to forecast mental healthcare history based on these factors and examine physical activities and mental health impact on healthcare. Our proposed machine learning method, Random Forest, has demonstrated remarkable accuracy of 88%, while the deep learning model, TabNet-Transform, has achieved an impressive accuracy of 90%. Our Model play key role in enhancing mental well-being and controlling certain psychoneurological disorders.
Keywords: Physical education, Smart healthcare, Artificial intelligent, Mental healthcare, Machine learning.

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INTRODUCTION

Mental healthcare is still a significant health issue globally resulting in numerous diseases and deaths hence stressing the healthcare systems and societies at large. However, mental healthcare has become more common despite advances in medical care and preventions of it. This show the importance of being proactive with regard to risk assessment and management. To minimize the incidence and severity of mental health, it is essential to identify individuals at high risk of suffering from heart disease so as to initiate appropriate treatments for them. Over the years, there has been increasing interest in artificial intelligence (AI) and machine learning (ML) to predict who will have heart disease and stop it (Adedinsewo et al., 2022). Vast and complex medical information may be analysed by using advanced tools like artificial intelligence (AI) and machine learning. They enable customized risk evaluations and therapies for every patient by combining several risk factors. Medical personnel may employ AI-powered prediction models to improve decision-making and resource management. These tools give better patient treatment and general community health results (Shu et al., 2021). AI base tools are helpful for early diseased identification. Physical activities are very important for good health. Predictive analytics and artificial intelligence (AI) have advanced tools to increase physical activity for heart health. Large, complicated data sets may be analysed by AI tools, which can also reveal patterns and insights that are invisible to humans. This enables us to develop extremely precise models that evaluate a person's risk of heart disease. The recommendations for physical exercise can be improved and adjusted over time to sophisticated AI-based algorithms. They provide more effective and long-lasting personalized therapies by gathering real-time data and improving prediction models. These customized methods enhance cardiovascular health (Krittanawong et al., 2018; Lopes, 2021). The main purpose of this study is to determine how well AI models work in predicting and enhancing physical activity levels that promote heart health. We will make use of a small amount of dataset that contains personal information, medical history, daily schedules, and living conditions. We developed model that can precisely identify who is at risk of heart disease based on their unique attributes and level of activity using machine learning and deep learning techniques. We will also examine the relationship between heart health, the environment, and lifestyle choices, as well as how physical exercise influences the risk of heart disease.

This study demonstrates how many risk factors impact the results of heart disease, which infectious disease in our understanding of its causes. These results can be applied to the development of evidence-based strategies for heart disease prevention. Physicians, public health professionals, and everyone attempting to make healthy decisions should all take help form this information. We may make better decisions to maintain our health and lower the global heart disease rate by being aware of these risk factors. Furthermore, the insights offered by this model may be linked into fitness applications and wearables to deliver individualized health advice in real-time. Engaging in physical exercise is not only important for the proper functioning of the heart, but it also contributes a great deal in improving one's state of the mind. Studies indicate that regular participation in sporting activities minimizes anxiety, depression and stress levels as it triggers the production of endorphins and advances brain functionality. Other than that, physical training is also beneficial in the maintenance of cognitive health and may even postpone the aging related brain disorders like depression, anxiety, Alzheimer's and other types of dementia. This relationship between mental health and fitness creates a rationale for activity plans that seek to enhance physical as well as mental endurance. In the advancements of medical field, heart disease is notwithstanding becoming more common; highlight the need for greater preventive measures. Among its many benefits, exercise is essential for both managing and preventing heart disease. Recommend the right sort and intensity of exercise for a particular individual depending on their age, gender, and lifestyle is provocative. It's likely that the way these variables combine to raise cardiovascular risk is not adequately taken into consideration by established guidelines. This grandness the need for targeted, customized therapies that modify physical activity guidelines based on each person's unique needs and characteristics. In this article we find that the physical exercise is import for the reduction of heart disease. The contribution of this study is:

- To develop an AI base model to provide personalized mental health and heart disease risk, this is based on individual.
- Developed a comprehensive dataset which encompassed demographics, medical history, lifestyle and environmental factors.
- Compared AI models, and RF and TabNet get very good accuracy, 88% and 90%.
- Guideline and future direction on mental healthcare, physical activities and heart disease.

Related work

Artificial intelligence and heart failure have been the subject of recent research that have explored a range of topics, from risk prediction to customized therapies. The development and testing of AI-based tools to estimate cardiovascular risk is one crucial field (Kagiyama et al., 2019). For example, to properly forecast the likelihood of future cardiac issues, researchers have used machine learning to analyses vast datasets of demographics, medical history, and lifestyle variables (Mathur et al., 2020). These models have outperformed conventional risk assessment instruments, indicating that artificial intelligence may help us better identify vulnerable individuals and create preventative strategies. Some old studies investigate how AI-based therapies might improve heart health and encourage physical activity. In this study author use sensors, wearable technology, and smartphone applications to assess activity, provide real-time feedback, and design individualized workout regimens. According to studies, these treatments successfully improve cardiovascular fitness, promote adherence to exercise guidelines, and reduce risk factors for cardiovascular problems such as obesity, high blood pressure, and raised cholesterol (Krittanawong et al., 2017).

In some recent studies researchers have used artificial intelligence to customize treatment plans for individuals who have already received a diagnosis in addition to predicting and intervening in cardiovascular diseases (Sermesant et al., 2021). AI systems evaluate intricate medical imaging data, including cardiac MRI scans and echocardiograms, to assist in the diagnosis and prognostication of cardiovascular disorders. Artificial intelligence-based decision support systems also assist medical professionals in choosing the best courses of action and maximizing drug schedules according to the unique needs and treatment outcomes of each patient (Vijayakumar et al., 2023). Artificial intelligence has the ability to significantly change preventative cardiac care (Addissouky et al., 2024). It enables more effective treatment plans, tailored treatments, and individual risk assessments. Nevertheless, more study is necessary to verify the long-term advantages, viability, and affordability of artificial intelligence in actual therapeutic settings. Resolving ethical, legal, and privacy concerns associated with the widespread application of artificial intelligence in cardiovascular care is also crucial (Pesapane et al., 2018; Said et al., 2022).

METHOD

Proposed system

The strategy adopted in changing healthcare education enables precise surveillance and forecasting through the use of IoT sensor apparatus, well enshrined machine learning algorithms and the most recent deep learning frameworks. The system is supported by the use of IoT wearables that include; smart wrist lets clothes, shoes and spectacles among others which all help in gathering and monitoring key health and performance parameters in real time. Such devices come with mobile phone connectivity for easy data transfer to the internet and most importantly to the cloud. This connected system allows for monitoring, availability and movement in the system, bringing about interaction between the educators and learners. This system increases the scale and efficiency of operations and provides the healthcare trainers with empirical evidence-based data for conduct focused on improving the results. A multi-layered architecture that consists of a machine learning algorithm and deep learning models is used to process and analyse the collected data in the system. Initially, the data coming from IoT devices, also referred to as the raw data is fed into a preprocessing stage where noise is removed and relevant features are extracted. In addition, deep learning approach goes a step further to analyse the data of which helps in making predictions accurately as well. This hybrid way of training has ensured that the health care training programs are flexible, effective and allows the provision of support that is individualized to the user. Figure 1 shows the detail steps of data collection and applying ML and deep learning models. This is a major step forward in the use of Artificial Intelligence in health care as well as training and coaching athletes.

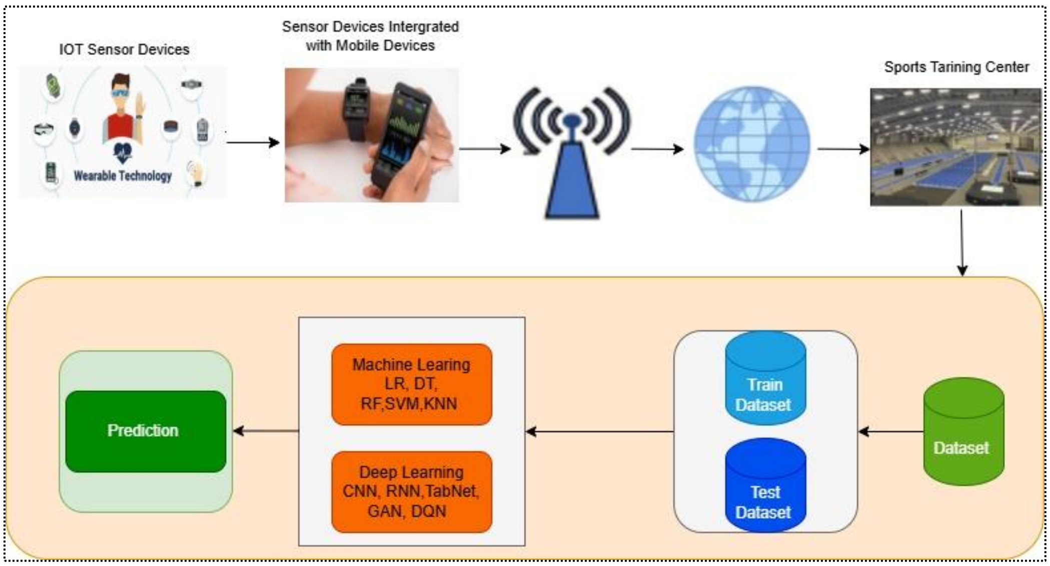

Figure 1. Proposed method flow diagram and collection of sport datasets.

To determine the risk of mental healthcare based on physical activities using your data-set, we recommend exploring a range of deep learning architectures. The data-set contains structured data (like participant demographics and physiological measurements) and sequential data (like physical activity details), a hybrid approach using multiple models may be effective. Here are some machine learning and deep learning models to consider: Logistic regression is a common statistical tool for predicting binary outcomes (e.g., yes/no, true/false). Despite the term regression it's actually a linear model that estimates the likelihood of a specific outcome based on input variables. Logistic regression models data with a sigmoid curve, transforming input values into probabilities. It uses maximum likelihood estimation to determine the weights (coefficients) of the input variables. Notably, it supports both categorical (non-numeric) and continuous (numeric) input variables. It's efficient, easy to interpret, and can handle noisy data. However, it assumes a linear relationship between the input variables and the probability of the outcome, which may not always be accurate (Said et al., 2022).

Decision Trees are a method for supervised learning that don't need any parameters. They can be used to classify and predict data. They work by breaking down the data into smaller groups based on the features and values. Each group is shown as a node in the tree. At each node, the algorithm picks the feature that makes the best split in the data, which makes the subsets as different as possible. Decision Trees are easy to understand which makes them good for knowing how the model makes decisions. But they can easily overfit the data, especially if the tree is too deep (Ville, 2013). Random Forest is a technique that combines many decision trees during training. It produces a result by finding the most common prediction (for classification) or the average prediction (for regression) from all the trees. Each tree in the forest uses a unique portion of the training data and a random selection of features, which reduces overfitting and improves accuracy. Random Forests are versatile, resilient, and less affected by noise than individual decision trees. They excel in various tasks like classifying, predicting, choosing important features, and finding unusual data points. However, they can take time to train and need fine-tuning of parameters like the number of trees and their maximum depth (Biau & Scornet, 2015). Convolutional Neural Networks (CNNs) are designed for image recognition and computer vision applications. They automatically learn features from raw pixel data, especially effective for grid-like data like images. By using convolutional layers and pooling layers, CNNs identify meaningful features and spatial relationships within images. This capability makes them ideal for tasks such as object detection, facial recognition, and medical image analysis, where spatial understanding is essential (Albawi et al., 2017; Dey & Salem, 2017; Jain & Medsker, 1999; Liu et al., 2021). In Figure 2, we have the following steps: physical activity data, pre-processing the data in the second and third stages of fracture engineering and fracture encoding, four-step machine learning model selection, training the data, model evaluation, fine-tuning the model, and finally predicting the illness. Similarly, for deep learning, we use the steps.

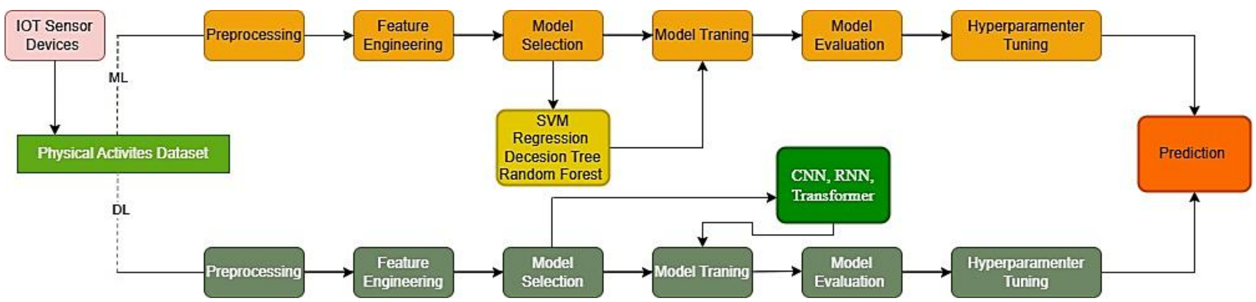

Figure 2. Detail steps of machine and deep learning steps.

Data set

Dataset is available of 100 peoples and provides extensive details on their lifestyle, medical history, demographics, and environmental factors. Their age, gender, socioeconomic background, ethnicity, and medical history (such as heart disease, hypertension, or diabetes) are all included. The dataset also explores lifestyle aspects including food, alcohol use, smoking behaviours, and physical exercise (kind, duration, intensity, and frequency). The dataset analysis reveals that the individuals are from diverse backgrounds. Their ages span a broad age range, from 35 to 65. Because both sexes are equally represented, if necessary, researchers can do gender-specific data analysis. The socioeconomic position and ethnicity data in the dataset enable researchers to investigate possible variations in heart disease risk across different demographic groups. Interestingly, a sizable portion of participants have a history of diabetes, high blood pressure, or heart disease, suggesting that the study population is more likely to experience cardiovascular issues. People differ greatly in their decisions, including what they eat, how much exercise they get, and whether or not they smoke. Their risk of heart disease is impacted by these variations. Additionally, environmental elements such as temperature, humidity, and air quality might affect heart health. In this article we used all features as X columns and predicted Y value is used for heart disease.

Data loading and pre-processing

Data set is in CVS format into a Pandas DataFram, it is a popular Python data processing tool and it is the process of loading data. Participant data including demographics, medical history, lifestyle choices, and heart disease status are often included in this dataset. In the preparation procedures we imputation or removal are used to deal with missing values. We also used label encoding to translate categorical data (such as gender and ethnicity) into numerical values. For scaling numerical characteristics to a constant range ensures that the predictions of the model are not greatly impacted by a single feature.

Model selection and training

Model selection is very important, in this article; we used machine learning models such as logistic regression, decision trees, random forests, and support vector machines (SVM) for classification problems. These techniques are chosen on the basis of things like efficiency, simplicity, and interpretability. We use deep learning models, such as feed forward neural networks (FNN), convolutional neural networks (CNN), and recurrent neural networks (RNN), for complicated tasks like medical diagnosis. Frameworks like as TensorFlow and PyTorch are used in the construction of these models. They have the capacity to identify complex links and patterns in data. In order to train the model's, pre-processed data is used. The goal variable (y), which denotes a history of heart disease, and the input characteristics (X) are fed into the model iteratively.

Model evaluation

In this article, we evaluate the performance of different models. Model performance is evaluated using a variety of metric. The area under the ROC curve (AUC-ROC), recall, accuracy, precision, and F1-score we used these metrics to assess a classification model's efficacy. The model's performance is displayed in a confusion matrix. It displays the number of times the model recognized an object properly, the number of times it misidentified an object, and the number of times it missed an object. Table 1 and 2 shows us how effectively the model can distinguish between objects and identify any trends in the errors that have been made.

Performance comparison

For compression of performance, we used different performance metrics in this article, we used Accuracy, precision recall and F1-Sscor etc., the optimal model for predicting the history of heart disease is determined by evaluating many models. Accuracy scores and confusion matrices for every model are looked at in order to achieve this. Experts may compare these performance metrics to decide which model is the most effective overall, with the highest sensitivity, specificity, and accuracy. Following equations 1 through 6 are used together with other performance measured (B Padmaja, 2021; Francis et al., 2023; Tiwari & Waoo, 2024; Yapıcı & Topaloğlu, 2021).

$$\mathrm{ACC} = \frac{TP+FP}{TP+FP+TN+FN} \tag{1}$$

$$\mathrm{Precision\ (P)} = \frac{TP}{TP+FP} \tag{2}$$

$$\mathrm{Recall\ (R)} = \frac{TP}{TP+FN} \tag{3}$$

$$\mathrm{F1-Score} = \frac{2*P*R}{P+FR} \tag{4}$$

$$Specificity = \frac{TN}{TN+FP} \tag{5}$$

$$\mathrm{Sensitivity} = \mathrm{Recall\ (R)} = \frac{TP}{TP+FN} \tag{6}$$

Hyper-parameter tuning and optimization

In proposed method, we have tuned our model by using hyper parameter. Hyper parameter tuning is adjusting a model's parameters to improve performance. To identify the ideal mix, grid search, random search, and Bayesian optimization facilitate effective exploration of various parameters. Models' ability to predict outcomes is improved by adjusting these parameters, which results in estimations of heart disease history that are more precise. Based on a variety of participant characteristics and lifestyle variables, the given code builds models that predict heart disease using machine learning and deep learning approaches. The algorithm attempts to generate strong models for predicting heart disease history through training, optimization, model selection, and data preparation.

Algorithm

Detail steps of proposed algorithm are given, Algorithm 1 used data of physical fitness to anticipate the risk of heart disease. In order to improve modelling and ensure consistency, it begins by correcting missing values in the data and standardizing its characteristics. To enable quick model building and performance evaluations, the data is split into distinct training, validation, and testing sets. Several machine and deep learning techniques are used to train and data throughout the model exploration and training phases. Machine and deep learning models are Logistic Regression, Decision Trees, SVM, K-NN, Convolutional Neural Networks, RNN, and Transformers. Every model is assessed separately and optimized based on pertinent metrics and predicted accuracy. All models, the procedure proceeds to the model assessment phase, when each model's accuracy, precision, and recall are evaluated.

Table 1. Algorithm 1 description.

Input: Physical fitness data **(X)**
Output: Predicted cardiovascular disease **(y) target Label**
Data Pre-processing: Handle missing values and normalize features. $X_{processed}$ = **Impute(X)** $X_{normalized} = X{-}\mu X / \sigma X$ Split the data into training, validation, and test sets. $(X_{train}, X_{val}, X_{test}), (y_{train}, y_{val}, y_{test})$ = **TrainTestSplit** $(X_{normalized}, y)$
Model Selection and Training: Select models for each model in [LR, DT, RF, SVM, KNN, CNN, RNN, Transformer] **M = [LR, DT, RF, SVM, KNN, CNN, RNN, Transformer]** Train each model on the training set: for each model in [LR, DT, RF, SVM, KNN, CNN, RNN, Transformer]: $y\hat{}_{train}$ = **Train** $(X_{train}, y_{train}, m)\ \ \forall m \in M$ Train model on training data
Model Evaluation: Evaluate the performance metrics (e.g., accuracy, precision, recall). **Evaluate(m)** = $(Acc_m, P_m, R_m, F_m, S_m, Spm)$ Select the best-performing model based on validation metrics. M_{best} = **argmax Evaluate(m)**
Final Model Testing: Test the selected model on the test set to assess its performance on unseen data. Evaluate model performance using various metrics and analyse predictions. **Evaluate on Test Set** = $(Accm_{best}, Pm_{best}, Rm_{best}, Fm_{best}, Sm_{best}, Spm_{best})$
Output: Trained model for predicting cardiovascular disease risk based on physical fitness data (y). $Y = m_{best}$

The model that performs the best during validation is selected, guaranteeing that it can process fresh data efficiently. Lastly, a test set is used to objectively assess the selected model's performance on untested data. Assesses the model's performance using a variety of criteria and verifies the accuracy of its predictions. Through a rigorous procedure, a trained model is created that may use physical fitness data to predict the risk of cardiovascular disease, making it a valuable tool for early identification and preventative healthcare measures.

Experiments

Data analysis was employed in the study to examine the intricate relationships between many variables and the risk of heart disease. Based on a variety of patient factors, prior heart disease was predicted using machine learning techniques. These techniques worked well and correctly classified the patients. The models demonstrated the usefulness of AI for heart disease risk prediction by taking into account variables such as age, gender, socioeconomic position, physical activity, and environmental circumstances. Through machine learning and DL, we can accurately predict the heart disease risk. Results of proposed heart diseased method are given in Tables, 2 and 3.

In this article we found that people who exercise regularly have a lower risk of heart disease. Activities like running, cycling, swimming, and walking can help reduce this risk. Exercise is an important way to keep your heart healthy, and it should be part of any plan to prevent heart disease. The study also found that there are several things you can change about your lifestyle that can help lower your risk of heart disease. Unhealthy habits like smoking, eating poorly, drinking too much alcohol, having a high body mass index (BMI), and unhealthy blood pressure and cholesterol levels are strongly linked to higher rates of heart disease. By promoting better decisions and lifestyle modifications, this highlights the necessity of concentrating on lifestyle-related aspects in health treatments. The study also demonstrates the influence of environment, lifestyle, and demography on cardiovascular health. Healthcare providers and legislators may develop more focused and efficient heart disease prevention and treatment strategies by having a better understanding of these links. Integrating clinical, behavioural, and environmental therapies into all-encompassing strategies to combat heart disease and improve public health. AI-powered prediction and data analytic empower healthcare professionals with more accurate risk predictions and earlier detection. Targeted interventions can result in better cardiovascular health for individuals and communities. A holistic approach prioritizes both personal and public health initiatives to prevent heart disease effectively.

Table 2. Machine learning models for matric measurement.

ML models	Accuracy	Precision	Recall	F-Score	Sensitivity	Specificity
Logistic regression	0.82	0.79	0.85	0.81	0.85	0.79
Decision tree	0.76	0.78	0.72	0.75	0.72	0.78
Random forest	0.88	0.85	0.92	0.88	0.92	0.85
Support vector machine	0.71	0.68	0.75	0.70	0.75	0.68
K-Nearest neighbours	0.79	0.81	0.76	0.79	0.76	0.81

Table 2 displays the performance of five traditional machine learning models used to predict the risk of heart disease using a wide-ranging dataset. Each model is based on a unique approach to classification, employing various algorithms and methods. Logistic Regression stands out with an accuracy of 0.82, highlighting its efficacy in classifying binary outcomes. Its precision of 0.79 and recall of 0.85 indicate its ability to minimize both false positives and false negatives, making it valuable in medical diagnostics where both are important factors. Tree-based models provide different approaches for disease classification. Decision Tree has a slightly lower accuracy (0.76) than Logistic Regression but still maintains a high precision (0.78) and recall

(0.72). Random Forest performs better, with an accuracy of 0.88, utilizing ensemble learning to combine multiple decision trees. It excels in recall (0.92), efficiently detecting instances of heart disease. Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) have lower accuracies (0.71 and 0.79 respectively), indicating they may not be ideal for this dataset.

Table 3. Deep learning models for metrics measurement.

Deep learning models	Accuracy	Precision	Recall	F-Score	Sensitivity	Specificity
Convolutional Neural Network (CNN)	0.85	0.83	0.88	0.85	0.88	0.83
Recurrent Neural Network (RNN)	0.81	0.79	0.83	0.80	0.83	0.79
TabNet- Transform	0.90	0.87	0.92	0.89	0.92	0.87
Generative Adversarial Network (GAN)	0.78	0.76	0.80	0.77	0.80	0.76
Deep Q-Network (DQN)	0.86	0.82	0.86	0.83	0.86	0.82

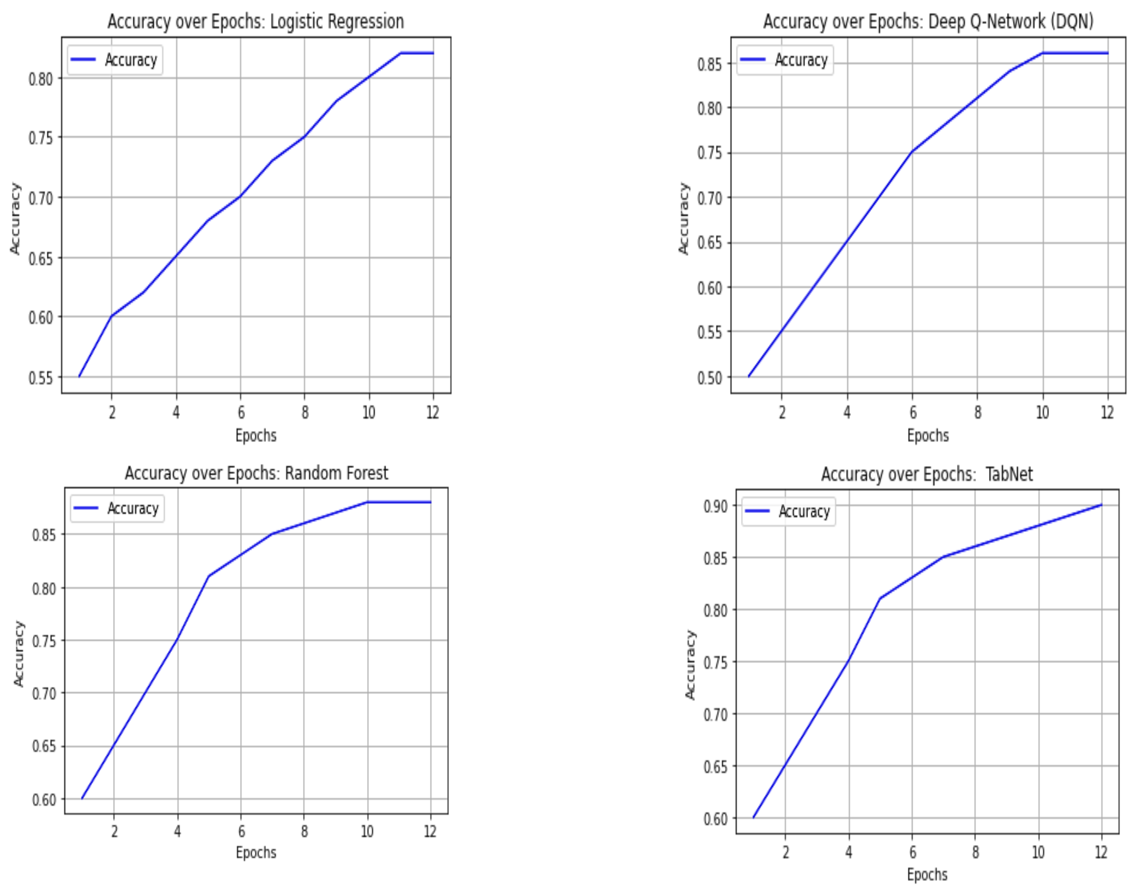

Figure 3: Predicted Accuracy: (a) machine learning models accuracy of logistic regression and model random forest (b) predicted accuracy of deep learning models Deep Q-Network (DQN) and TabNet.

Table 3 shows how well five different deep learning models predicted the risk of heart disease using a large dataset. Each model has a different structure designed to handle different types of data and tasks. The accuracy of the Convolutional Neural Network (CNN) is 85%. This model is best at finding patterns in images and other spatial data, such as medical images or sensor data. The Recurrent Neural Network (RNN) has an accuracy of 81%. This model is best at understanding patterns in time-series data, such as patient histories, because it can process data in order. Among the models, the Transformer surpasses all with an accuracy of

0.90. It effectively captures long-range relationships and context in the data, making it well-suited for both structured and unstructured healthcare data. The Generative Adversarial Network (GAN) and Deep Q-Network (DQN) have slightly lower accuracies of 0.78 and 0.86, respectively. GANs, typically used for synthetic data generation, can also be used for classification with their discriminator component. DQNs excel in reinforcement learning. Choosing the right deep learning model is crucial for achieving the best predictive results in healthcare analytics. The Figure 3 shows a variety of models that can handle different types of data and tasks, highlighting the need for careful selection based on specific requirements.

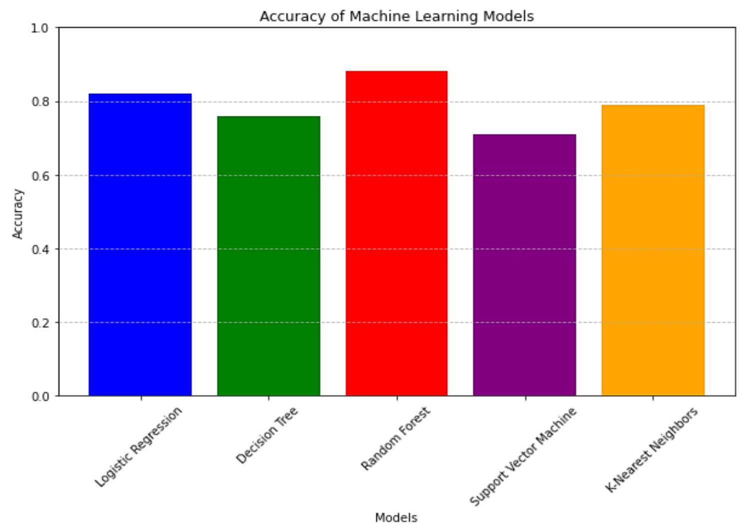

Figure 4. Predicted accuracy of machine learning models.

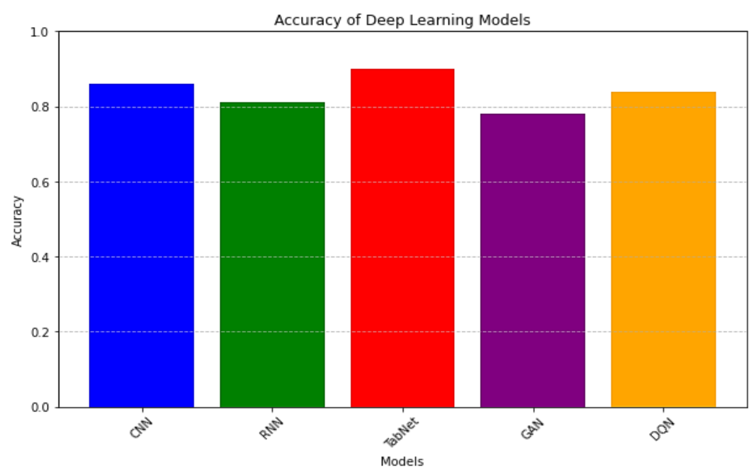

Figure 5. Predicted accuracy of deep learning models.

The TabNet-Transformer versus Random Forest confusion matrix shows strong performance in predicting cardiovascular disease risk. These two classifiers presented high sensitivity and specificity; thus, TabNet has a very high accuracy (0.90), precision (0.87), and recall (0.92) values, as shown. Further, Random Forest has obtained an accuracy of 0.88, precision of 0.85, and recall of 0.92 against confusion matrices. These matrices as well have a considerably low number of false positive counts and false negatives, shown in Figure 4,5. Thus, it will be a reliable classification. Regarding the evaluation of models with ROC curves, both

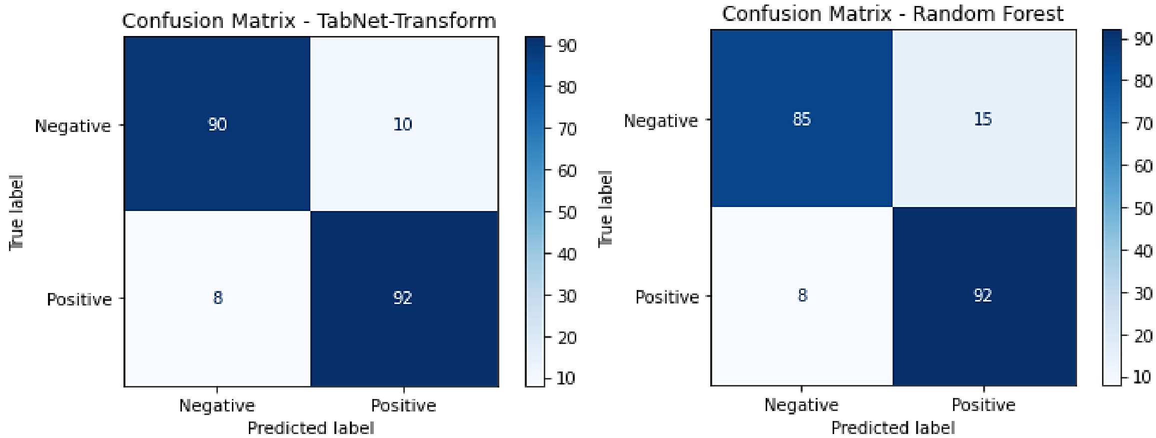

Figure 6. Confusion matrix of highly predicted accuracy model of DL and machine learning.

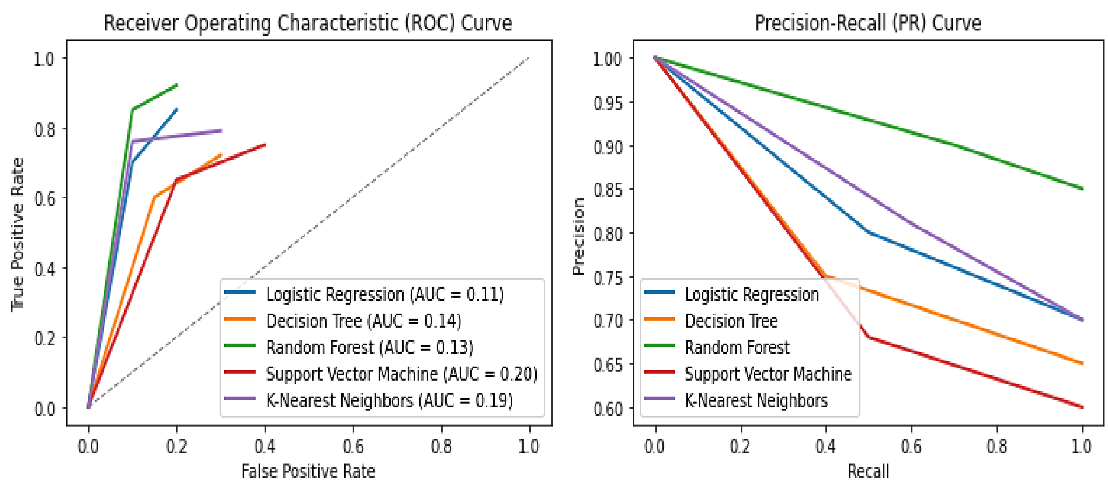

Figure 7. Results of machine learning models, ROC and PC Curve.

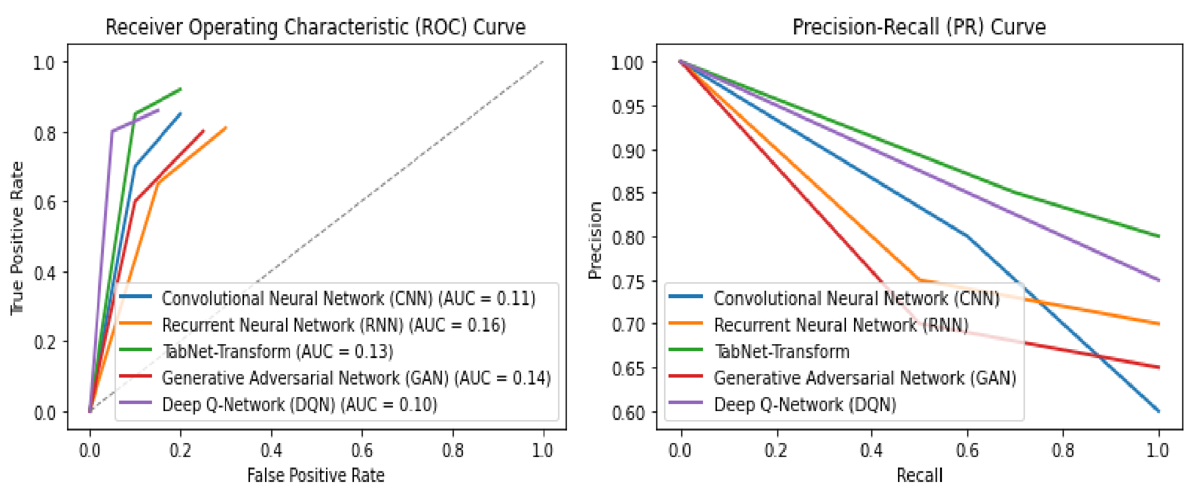

Figure 8. Results of Deep learning models, ROC and PC Curve.

TabNet and Random Forest obtained very high AUC scores, where TabNet performed a little bit better in the AUC part than Random Forest, indicating an excellent ability to discriminate between positive and negative cases of cardiovascular diseases. TabNet again showed its superiority over other models with a markedly better precision and recall in the Precision Recall (PR) curve analysis. This indicates that it effectively minimizes both false positives and false negatives, which is important in medical diagnosis. The ROC and PR curves for machine learning and deep learning models also highlight the excellent performance of TabNet and Random Forest, emerging as two leading candidates for accurate heart disease risk prediction. Figure 6 shows the confusion matrix of random forest and TabNet-Transformer, and Figure 7 shows the detailed comparison of machine learning models, ROC and PR curve and Figure 8 shows the comparison of deep learning models ROC and PR curve.

DISCUSSIONS AND RECOMMENDATIONS

From this study following important points are found, important conclusions from this study point the way for forecasting and avoiding mental healthcare sickness. First it highlights the necessity of a thorough evaluation of heart health that takes into account one's environment, lifestyle, medical history, and habits. These diverse elements contribute to the development of more accurate prediction models, which in turn enable the creation of individualized risk assessments and focused treatments for those who are more vulnerable. The substantial association between physical exercise and a lower risk of heart disease is another important discovery. Regular participation in moderate-to high-intensity physical exercise is associated with a decreased incidence of heart disease, highlighting the preventive role of this activity.

Developing individualized programmers to encourage regular exercise and overcome barriers can greatly lower the incidence of heart disease. Furthermore, our findings indicate that environmental factors such as temperature and air quality can influence heart health, emphasizing the need for more study (B Padmaja, 2021). In order to inform policies that lower environmental hazards and support healthy living circumstances, further study is required to fully comprehend the relationships between environmental variables and heart health. Our conclusions lead us to the following recommendations: 1. Testing prediction models on a variety of populations to increase their utility and accuracy. 2. Giving priority to programmers' that promote physical exercise on a personal, social, and legislative level. Urban planning and the implementation of tested policies are critical environmental elements that must be changed to support heart health. This reduces the risk of cardiovascular disease and contributes to healthier communities. Researchers, leaders, medical professionals, and community people may all learn more about avoiding heart disease and develop better ways to enhance heart health and general well-being by collaborating across disciplines (Fatima, 2024; Francis et al., 2023; Vajjhala & Eappen, 2024).

The provided dataset includes a wide range of information about people's health that could be linked to heart disease. It includes demographics like age, gender, race, and socioeconomic status, as well as health indicators like cholesterol, blood pressure, and how well their heart responds to stress. The dataset also includes information about their lifestyle, such as how often they exercise, how hard they exercise, and what types of exercise they do. It also includes information about the environment they live in, like the air quality, temperature, and humidity. This dataset can be used by researchers to better understand the causes of heart disease and find the most important risk factors. By employing sophisticated methodologies such as machine learning and deep learning on this dataset, scholars might uncover intricate patterns and connections that may not be readily apparent through conventional statistical procedures. Using the provided data, supervised learning models, for instance, may be trained to identify the primary predictors and risk factors and determine if a person has a history of heart disease. Deep learning models can reveal hidden patterns in the dataset and hitherto undiscovered correlations between variables since they automatically learn the hierarchical representations of the data. Additionally, researchers may better understand how well various algorithms perform by visualizing model performance using confusion matrices and accuracy plots. Academics can assess a variety of variables, including accuracy, precision, recall, and others, with the use of confusion matrices. They show the model's prediction accuracy for different classes. By using deep learning and machine learning techniques to this data, we might be able to better understand the risk factors for heart disease and provide individualized prevention regimens(Dey et al., 2024; Rahman et al., 2024; Vajjhala & Eappen, 2024).

AI prediction models are precise and personalized; they may tailor workout recommendations based on particular characteristics, optimizing cardiovascular outcomes. With the use of large datasets and complex algorithms, artificial intelligence (AI) may improve the accuracy of treatments by taking into account variables like genes, socioeconomic position, and environmental impacts. To ensure effectiveness, future research should improve prediction models and assess their performance across different populations. AI algorithms enable physical activity treatments to get real-time input and adjust accordingly. This allows for real-time feedback and adaptation. By constantly analysing data and changing recommendations based on individuals' reactions, AI-driven platforms can increase adherence to and the effectiveness of the intervention. However, to maximize adoption and accessibility, it is important to develop user-friendly interfaces and smoothly integrate AI technology into current healthcare processes to maximize adoption and accessibility. It is critical to protect patient privacy, ensure data security, and prevent prejudice. Transparent communication and strict governance are essential for maintaining trust and encouraging the responsible use of AI in this field. Paraphrased Text, Collaboration for AI Guidelines, Government agencies should work with healthcare professionals to create rules and best practices for developing, using, and testing AI in heart disease care. Multi-Disciplinary Integration, to use AI tools effectively, people in cardiology, data science, psychology, and public health need to work together. Discussions around AI for Human Learning and Behaviour Change through Physical Fitness will remain limited if there is no recognition of how AI provides cues that encourage individuals to be proactive in managing their health. The importance of measuring heart rate, amount of activity, or even the change in VO2 Max in assessing fitness levels provides such information to the AI models which can, therefore, predict heart diseases in patients much earlier creating a feedback loop that modifies behaviour for health promotion. Such modification of behaviour is also facilitated through health-related behaviour modification approaches where the patient is given information directly about their health status and personal conduct and how that modifies their exercise, dietary or general lifestyle patterns. It is also important to note that when fitness gadgets are being worn or their respective software used, it is possible to advise on change of behaviour at any particular time that warrants such a change, which aids in enhancing the desired behaviours and ensuring behaviour change is achieved in the long haul. Incorporating this type of support not only assists the participants in becoming proficient in health education but also develops their interest in healthier practices thus possibly reducing the chances of developing cardiovascular diseases in the years to come.

Combining AI with diverse skill teams can improve collaboration, information sharing, and patient outcomes. Knowledge and Creativity, Schools should provide programmers' where professionals from many professions may learn from one another and possibilities for collaborative research in order to foster innovative thinking and collaboration in the prevention of heart disease. It's critical to employ trustworthy outcome indicators, such as cardiovascular events, quality of life, and healthcare utilization, in order to fully evaluate the effects of AI technology. Economic analyses are also required to determine the worth of AI-driven interventions and direct the distribution of resources. AI has the potential to transform preventive cardiology by boosting cardiovascular health, optimizing medications, and customizing recommendations for physical exercise. But in order to realize AI's full potential, implementation, ethical, and legal issues must be resolved. Cooperation, openness, and long-term assessment planning are necessary to guarantee that AI-driven therapies successfully improve cardiovascular outcomes. The main points of discussion and recommendation are:

- Need of comprehensive risk assessment for heart health of each individual, environmental, lifestyle, medical and habitual factors.
- Need to highlight the link between regular moderate to high intensity exercise, which can reduce heart disease risk.
- Environmental influences are most important factor, the temperature and air quality on heart health, it can be considered for further research.
- To develop a recommendation system, which can use for testing, promoting exercise programs and it will be helpful for urban peoples to improve heart health.

Mental healthcare

The benefits of physical exercise on mental health have been acknowledged more and more, not only in prevention but also in cure. Physical exercises, especially performed regularly, help to release endorphins and neurotransmitters such as serotonin and dopamine, which are responsible for mood stabilization and lowering anxiety as well as depression levels. In addition, everyday aerobic activities such as walking, running, or riding a bicycle have a positive effect on cognitive abilities as well as on resistance to emotional disturbances. The AI models used in this research pointed out consistent associations between physical exercise and lower levels of psychological distress, indicating that properly designed exercises can be a beneficial strategy to enhance one's state of mind. Such observations justify exercise-oriented schemes in health management and illustrate the importance of physical activity in mental health preservation. Physical activities not only enhance mental health but can be beneficial in treating ailments related to the brain as well. Regular exercises have been proven to increase the process called neuroplasticity that some of the neurodegenerative disorders like Alzheimer's, anxiety, depression, epilepsy, and Parkinsons may not progress quickly. The result of the analysis revealed that those individuals who maintained a regular exercise took appeared to perform better on the cognitive markers and had fewer declines due to age. This way of integrating AI models turns out to help us understand how particular patterns of physical exercises affect the state of the brain with regards to neurological health creating room for such interventions to be tailored to individuals. This kind of management helps to promote even the prevention of diseases through better health education and practice (Dey et al., 2024; Fatima, 2024; Francis et al., 2023; Rahman et al., 2024; Tiwari & Waoo, 2024; Vajjhala & Eappen, 2024).

Future direction

Our findings pave the way for further investigations mental healthcare and prognosis. We may include data from wearable devices or genetic markers into these algorithms to improve their ability to forecast the risk of heart disease. This will enable us to determine the population most vulnerable to heart disease. Second, research into mental healthcare care prevention strategies, such as encouraging physical activity and leading healthier lives, is needed. Long-term research will provide insight into how long-term lifestyle modifications impact cardiovascular health. Using wearables and other digital technologies, physical activity and healthy habit compliance may be tracked in real time. Research insights can be gained from examining the complex interaction between environmental variables and heart health. Analysing the relationship between heart disease risk and environmental factors, such as air quality or climatic variations, can direct policy and urban planning initiatives towards the creation of healthier environments. To put initiatives that lower environmental dangers and build heart-friendly cities into action, academics, policymakers, and city planners must work together.

Improving heart disease prediction models, creating and executing lifestyle modifications, and investigating the influence of environmental variables on heart health should be the top priorities for future study. We may work to lower the global burden of heart disease and enhance people's general health by expanding our knowledge of the intricate causes of heart disease and putting research results into useful solutions. Furthermore, future research in preventive cardiology may benefit from focusing on enhancing precision medicine by using AI to customize therapies based on unique genetic profiles, biomarkers, and lifestyle variables. Multimodal Data Integration: Merging information from many sources (such as sensors, questionnaires, and medical records) is increasingly crucial for comprehending heart health risks and behaviours. To make this data more helpful for developing individualized treatment plans, researchers must devise new methods for integrating and analysing information using artificial intelligence (AI) tools. Interpretability and explainable AI, it's critical to make sure we can comprehend AI algorithms' inner workings and provide justification for their conclusions as they grow in complexity and are employed in healthcare more often. Researchers must devise techniques that improve the transparency, interpretability, and explainability of AI algorithms.

Future research can leverage AI, such as reinforcement learning and tailored nudges, to create personalized interventions that are effective, engaging, and long-lasting. AI-powered approaches in preventive cardiology can be tailored to individual needs and barriers by using principles from behavioural economics and psychology. To ensure fair access and acceptance of these approaches, bridging the gap between research and practice is crucial. Implementation Science in Future Studies; Future research should use principles from implementation science to find obstacles and factors that help the roll-out of interventions. Interventions should be, culturally sensitive, linguistically appropriate, accessible to marginalized populations, longitudinal monitoring and predictive analytic s, instead of just looking at risk factors at one time, future research should focus on creating AI systems that, continuously track people's heart health over time. Predict future risks based on these patterns. Future research direction can be explored in near future:

- Enhance and validate ML and DL models for better heart disease risk prediction.
- Study long-term effects of lifestyle changes on heart health with real-time monitoring.
- To develop a policy for heart disease risk and environmental factors.
- Exploring personalized AI tools for better healthcare recommendations.

AI-driven insights to further refine personalized exercise recommendations aimed at improving mental health and preventing neurological decline. Longitudinal studies with larger and more diverse populations are needed to validate the impact of specific types, durations, and intensities of physical exercise on mental well-being and cognitive resilience. Additionally, integrating data from wearables and fitness apps with AI models could provide real-time monitoring, enable early detection of mental health issues and offer timely, personalized interventions. This could revolutionize preventative healthcare by promoting both physical and psychological well-being through tailored fitness strategies.

CONCLUSIONS

This research explored the use of machine learning and deep learning models to forecast heart disease history based on various input factors. These models can help stratify risk and detect cardiovascular problems early, allowing for individualized healthcare interventions based on personal risk profiles. The study found a connection between physical activity and heart health; those who regularly engaged in moderate to vigorous exercise had lower heart disease rates. This emphasizes the importance of incorporating exercise into daily routines to reduce cardiovascular risks. Other demographic factors, such as age, gender, ethnicity, and socioeconomic status, were also considered in the study. Lifestyle choices such as diet, smoking habits, and alcohol consumption also showed associations with cardiovascular risk factors, highlighting the importance of addressing modifiable lifestyle factors in preventing heart disease. Developing research into therapeutic and preventative mental and heart disease therapies need strong cooperation with medical professionals and decision-makers. Together, we can create personalized plans that help individuals live heart-healthy lives by encouraging collaboration and information sharing. Optimizing AI implementation in conjunction with patients' physical activity data offers enormous prospects for enhancing cardiovascular health. Artificial intelligence models can allow making behavioural changes in individuals by turning the fitness numbers into healthy actionable insights and helping them take preventive measures against coronary artery disease. This combination of sophisticated analytics and live interactions holds a great promise in promoting sustainable behaviour change, which will not only benefit the individuals but also the general public health. Engaging in regular physical activity plays an important role in the enhancement of mental health and cognition, which in turn may reduce anxiety, depression, and neurological disorders. Improving these effects by applying AI models to tailor exercise recommendation is a plus, thus encouraging overall wellness.

AUTHOR CONTRIBUTIONS

W. J.: conceptualization, investigation, visualization, resources, supervision, funding acquisition. C. H.: resources, supervision, formal analysis, funding acquisition. R. A.: investigation, formal analysis, supervision, resources, project administration. M. S. I.: writing - original draft, funding acquisition, investigation, validation, supervision, formal analysis. M. B. B. H.: investigation, visualization, formal analysis, supervision, data curation.

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No potential conflict of interest was reported by the authors.

DATA AVAILABILITY STATEMENT

Data will be available at the author's request.

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